METHOD AND APPARATUS FOR COMPRESSING

MULTISPECTRAL IMAGES

BACKGROUND OF THE INVENTION

This invention relates to an image data compressing technology by which image data for a multispectral image reconstructed from a plurality of band images of an object captured in a wavelength range as divided into a plurality of bands can be efficiently compressed without impairing the quality of the image.

With the recent advances in digital image processing, it has become possible to provide a complete representation of image's color information (lightness, hue and saturation) by a multispectral image which carries spectral information for each of its pixels. To produce a multispectral image, an object is recorded in divided wavelength bands and on the basis of a multiband image consisting of the captured band images, the spectral reflectance distribution is estimated for each band image. The multiband image can reproduce the color information that cannot be fully represented by the conventional RGB color images consisting of red (R), green (G) and blue (B) images and will prove effective in the art world which

needs more accurate color reproduction. In order to make
the most of the capability for correct reproduction of
color information, the multispectral image is desirably
produced from a multiband image having as many bands as
possible, say, 41 bands which are obtained by dividing a
recording wavelength range of from 380 to 780 nm by 10 nm
or even 81 bands by dividing the range by 5 nm.

A problem with the multispectral image having spectral
information for each pixel is that it possesses spectral
reflectance data for each group of the channels, say, 41
channels, into which the recording wavelength range has
been divided and that compared to the conventional 3-
channel RGB color images, the volume of the required image
data is about 13 times as much (41/3). This means a large
storage capacity and a prolonged time are required to save
the image data for multispectral images. In addition, so
much time is taken to transfer the image data over a
communication network that great difficulty is involved in
data handling.

To deal with this situation, Keusen proposed an
improved technique in which spectral waveforms obtained
from spectral information for each of the pixels in a
multispectral image were expanded into three color matching

functions as of the RGB colorimetric system and those

portions of the spectral waveforms that could not be

expressed by color matching functions were expanded into

basis vectors by principal component analysis and those

principal components which were representative of the image

information for the spectral images were extracted and

adopted but other principal components were discarded so

that the spectral waveforms of interest were eventually

expressed by a total of six to eight basis vectors

including the color matching functions [Th. Keusen,

Multispectral Color System with an Encoding Format

Compatible with the Conventional Tristimulus Model, Journal

of Imaging Science and Technology 40: 510 to 515, (1996)].

In accordance with this method, the image data for the

multispectral image can be compressed by expressing the

spectral waveforms in terms of six to eight basis vectors

and their multispectral coefficients. In particular, if

the spectral waveforms are expressed by the color matching

functions of the RGB colorimetric system, their

coefficients are R, G and B tristimulus values and the

image can be directly sent for subsequent processing

without performing any special transformations in order to

provide compatibility for the conventional image processing

and display apparatus which employ the tristimulus values of R, G and B pixels. This is a great benefit to the purpose of reducing the volume of data processing.

If a multispectral image consisting of 41 spectral images is expressed by eight basis vectors and their multispectral coefficients according to the method described above, the image data to be handled can be compressed to about 20% of the initial volume (8/41 x 100). Compared to the RGB color image, the volume of the image data for the multispectral image composed of 41 spectral images is about 13 times as much and even if it is reduced to about 30% of the initial value by the Keusen method, the volume is still as much as about 2.5 times the image data for the RGB color image (13 x 20/100). As a result, the aforementioned problem of the prior art still remains and the time for recording and storing the image data on recording media as well as the time for transferring them over a communication network are long enough to present difficulty in data handling.

SUMMARY OF THE INVENTION

The present invention has been accomplished under these circumstances and has as an object providing a method

by which a multispectral image reconstructed from a
plurality of spectral images obtained by recording an
object in a wavelength range as divided into a plurality of
bands can be compressed at an increased ratio but without
causing visual deterioration and which thereby improves the
efficiency of image data handling.

Another object of the invention is to provide an
apparatus for implementing the method.

In order to attain the object descried above, the
present invention provides a method of compressing a
multispectral image composed of a plurality of spectral
images of an object captured in a wavelength range divided
into a plurality of bands, comprising the steps of
segmenting the multispectral image into a plurality of tile
images, performing principal component analysis on
respective tile images to obtain for each tile image a
principal component number of sets of principal component
vectors and principal component images for the
multispectral image, determining from the plurality of
sets, for each tile image, an optimum principal component
number of sets of optimum principal component vectors and
corresponding optimum principal component images that
optimally represent image information about the

multispectral image, and expressing compressed image data

for the multispectral image by means of at least the

optimum principal component number of sets of optimum

principal component images and optimum principal component

vectors for each tile image.

Preferably, the compressed image data for the

multispectral image are expressed not only by the optimum

principal component number of sets of the optimum principal

component images and the optimum principal component

vectors but also by tile image information having

information about tile numbers of the tile images, a tile

position and· an image size of the tile images.

Preferably, the optimum principal component number is

determined based on colorimetric values in a color space.

Preferably, the optimum principal component number is

a minimum principal component number at which an absolute

value of difference between image information about a

composite image that is composed of selected number of sets

of the principal component vectors and the principal

component images and the image information about an

original image that is composed based on the multispectral

image is below a specified value or an absolute value of

variation in error from the original image which is

presented when the composite image is determined by sequentially including in an order of contribution those principal component vectors which make greater contribution to the multispectral image does not exceed a predetermined value.

Preferably, an image size of the tile images in terms of pixel is expressed as a power notation of 2 in both a longitudinal and a transverse direction.

Preferably, the tile images all have an image size in terms of pixel.

In order to attain another object described above, the present invention provides an apparatus for compressing a multispectral image composed of a plurality of spectral images of an object captured in a wavelength range divided into a plurality of bands, comprising an image segmenting section for segmenting the multispectral image into a plurality of tile images, a principal component analyzing section in which respective tile images obtained in the image segmenting section are subjected to principal component analysis to obtain for each tile image a principal component number of sets of principal component vectors and principal component images for the multispectral image, and an optimum principal component

vector/image extracting section which determines an optimum

principal component number of sets of optimum principal

component vectors and optimum principal component images

that optimally represent image information about the

multispectral image from the principal component number of

sets of principal component vectors and principal component

images as obtained in the principal component analyzing

section, and wherein image data for the multispectral image

is compressed by expressing by means of at least the

optimum principal component vectors and the image data for

the optimum principal images for each tile image as

obtained in the optimum component vector/image extracting

section.

BRIEF DESCRIPTION OF THE DRAWINGS

Fig. 1 shows in conceptual form an exemplary

multispectral image acquisition system including the

multispectral image compressing apparatus according to the

second aspect of the invention;

Fig. 2 is a block diagram for an example of the

multispectral image compressing apparatus;

Fig. 3 illustrates how an image is segmented into tile

images in the practice of the multispectral image

compressing method according to the first aspect of the invention; and

Fig. 4 is a flowchart for an example of the multispectral image compressing method.

THE PREFERRED EMBODIMENT OF THE INVENTION

A multispectral image acquisition system for implementing the multispectral image compressing method according to the first aspect of the invention is described below in detail by reference to the preferred embodiment shown in the accompanying drawings.

Fig. 1 shows a multispectral image acquisition system for implementing the multispectral image compressing method according to the first aspect of the invention and which includes the multispectral image compressing apparatus according to the second aspect of the invention.

The multispectral image acquisition system (hereunder referred to simply as "the system") which is generally indicated by 10 takes a multispectral image of an object O and stores the captured image data on a recording medium. Its principal components are as follows: a light source 12 for illuminating the object O; a variable filter 14 for dividing the recording wavelength range into a plurality of

bands; a CCD camera 16 for taking a multiband image of the object O; a multiband image storage section 18 for saving the captured image data temporarily; a multispectral image acquisition unit 20 for reconstructing a multispectral image from the multiband image by estimating the spectral reflectance distribution for each pixel; a multispectral image compressing unit 22 for compressing the image data for the multispectral image at a higher ratio while suffering limited visual deterioration; and a recording medium drive unit 24 for saving the compressed image data. In the present invention, the multispectral image has preferably at least six channels of spectral images and, hence, at least six constituent wavelengths in the spectral reflectance distribution.

The light source 12 for illuminating the object O is not limited in any particular way as regards type and other factors; however, for the purpose of reconstructing a multispectral image from the captured multiband image by estimating the spectral reflectance distribution, the light source 12 is preferably one with a known spectral intensity distribution.

The variable filter 14 is a bandpass filter with which the recording wavelength range can be divided into a

variable number of bands, say, 16, 21, 41 or 81 bands for the purpose of capturing a multiband image of the object O. A useful example of the variable filter 14 is a liquid-crystal tunable filter.

The CCD camera 16 is a device with which the object O imaged by the light reflected from it to pass through the variable filter 14 so that it is segmented into a desired number of spectral wavelength bands is captured as black-and-white band images. The image-receiving plane of this camera has a planar array of CCDs (charge-coupled devices) as area sensors. For proper setting of the dynamic range for the lightness values of the image to be taken, the CCD camera 16 includes a mechanism for adjusting the white balance before taking the picture of the object O.

The multiband image data storage unit 18 is a site for temporary storage and saving of the multiband image composed of a plurality of band images that have been captured in the recording wavelength range as divided into multiple bands and which have the white balance adjusted in association with the respective bands.

The multispectral image acquisition unit 20 has one-dimensional look-up tables (1D LUTs) constructed preliminarily on the basis of the correspondence between

the image data for objects with known values of spectral reflectance that were captured with the CCD camera 16, for example, the image data for the gray patches on a Macbeth chart, and the known values of spectral reflectance. Using the 1D-LUTs and on the basis of the image data for the multiband image of the object O that have been retrieved from the multiband image data storage unit 18, the multispectral image acquisition unit 20 estimates the spectral reflectance of the object O for each pixel and acquires the multispectral image.

If the variable filter 14 has such filter characteristics that its spectral transmittance distribution partly overlaps between bands, the acquired multispectral image does not have a sharp enough spectral reflectance distribution to assure highly precise estimation of the spectral reflectance distribution of the object O. To avoid this problem, such filter characteristics may be eliminated by deconvolution through matrix operations and Fourier transformation.

In this way, the multispectral image having an n-wavelength spectral reflectance distribution as spectral information is acquired from the multiband image captured

with the aid of the variable filter 14 that divided the recording wavelength range into n bands.

The recording medium drive unit 24 records the image data for the multispectral image on various kinds of recording media such as hard disk, floppy disk, MO, CD-R and DVD after they have been compressed by the multispectral image compressing unit 22 to be described later. In addition to or in place of the recording medium drive unit 24, a network coupler may be installed so that the compressed multispectral image data to be described later can be transferred over a variety of communication networks.

The multispectral image compressing unit 22 is a site at which the multispectral image data that constitutes the multispectral image obtained by the multispectral image acquisition unit 20 is compressed at high ratio while suffering only limited visual deterioration. As shown in Fig. 2, the multispectral image compressing unit 22 comprises an image segmenting section 22a, a principal component analyzing section 22b and an optimum principal component vector/image extracting section 22c. If desired, the multispectral image compressing unit 22 may be composed

of software having the capabilities set forth below or it may be configured as a single hardware unit.

The image segmenting section 22a is a site where the image obtained by the multispectral image acquisition unit 20 is segmented into n_t tile images T_L (L = 1 to n_t). To give just one example, a multispectral image consisting of 1024 x 1024 pixels may be segmented into tile images T_L each consisting of 16 x 16 pixels. The size of tile images T_L must be such that their total number of the pixels in each tile image T_L is at least greater than the number of constituent wavelengths in the spectral reflectance distribution for each of the pixels in the multispectral image. If this condition is not met, highly precise principal component vectors cannot be determined in a principal component analysis to be discussed below.

Fig. 3 shows am example of segmenting the multispectral image into tile images T_L. In the illustrated case, the multispectral image is segmented in eight rows and eight columns to obtain 64 tile images T_L of identical size. Tile images of identical size permit easy processing in the analysis of principal components and the construction of image information that are to be discussed later. Preferably, the longitudinal and transverse sizes

of each tile image T_L are such that the number of pixels

can be expressed as a power notation of 2. This is in

order to provide convenience for retrieving the compressed

image data and performing necessary processing.

In the embodiment under discussion, all tile images T_L

are of the same size but this is not the sole case of the

invention and the size of tile images T_L may be varied as

appropriate for the contents of the image. For example, if

the background of the image is the sky, the ground or the

like that has small changes in hue, lightness or

saturation, the size of the tile images T_L in such

background may be increased; on the other hand, the tile

images T_L in a portion that includes the object and the

like which has marked changes in hue, lightness or

saturation may have a smaller size. Varying the tile image

size contributes to an enhanced compression ratio.

As long as the total number of pixels in each tile

image T_L is at least greater than the number of constituent

wavelengths, the size of the tile image T_L, its aspect

ratio and other factors are not limited in any particular

way.

The principal component analyzing section 22b is a

site where the principal components of the spectral

reflectance distribution possessed by each of the pixels in the tile images T_L (L = 1 to n_t) into which the multispectral image has been segmented are analyzed and the spectral reflectance distribution for each pixel is expanded into principal components. In the following discussion, the number of wavelength bands is assumed to be n.

The principal component analysis to be performed in the present invention is commonly called "optimum sampling" which is one of the methods for sampling a group of observed waveform data by expansion into orthonormalized basis functions. This is a method for providing the most precise representation of the observed waveform data by weighted averaging of the least number of orthogonal basis functions. In the following discussion, the orthogonal basis functions are called "principal component vectors".

A specific procedure for the principal component analysis to be performed in the present invention is this. On the basis of the observed waveform for each of the pixels in the tile images T_L (L = 1 to n_t) into which the multispectral image has been segmented, linearly independent eigenvectors that are inherent in the observed waveforms are determined as principal component vectors by

statistical and eigenvalue analyzing techniques. From the
thus determined principal component vectors, those
principal component vectors having such small eigenvalues
that would be reduced to zero if the observed waveforms had
no noise component are eliminated to determine a smaller
number of optimum principal component vectors than n, or
the number of wavelength bands. The observed waveforms are
linearly expressed by these optimum principal component
vectors. For details of this method, see "Kagaku Keisoku
no tameno Hakei Data Shori (Waveform Data Processing for
Scientific Measurement and Instrumentation)", ed. and
written by S. Minami, pp. from 220 to 225, CQ Publishing
Co., 1986. The principal component analysis is primarily
performed in the principal component analyzing section 22b
and the optimum principal component vector/image extracting
section 22c to be described later.

The principal component analysis is preferably
performed in the case where the observed spectral
reflectance waveform for each of the pixels in the tile
images T_L (L = 1 to n_t) into which the multispectral image
has been segmented can be expressed linearly and where the
noise component in that waveform is also independent of the
value of spectral reflectance.

We now describe the procedure of principal component analysis with particular reference being made to the embodiment under consideration. For each pixel, the tile images T_L ($L = 1$ to n_t) into which the multispectral image has been segmented have the values of spectral reflectance distribution R which are equal in number to n, or the number of bands into which the wavelength for recording the object has been divided by means of the variable filter 14. To be more specific, the tile images T_L have the spectral reflectance distribution R that has n constituent wavelengths corresponding to n bands and which consists of n values of spectral reflectance. In addition, the total number of pixels in the tile images T_L is greater than n, or the number of constituent wavelengths. Hence, by means of a statistical treatment that is independent of the pixel position in the images, namely, by expressing the spectral reflectance distribution $R(i,j,\lambda)$ in the form of an n-dimensional vector, i.e. $[R(i,j,\lambda_1), R(i,j,\lambda_2), R(i,j,\lambda_3), \cdots, R(i,j,\lambda_n)]^T$ (superscript T represents transposition, (i,j) the position of a pixel of interest, and λ the spectral wavelength) and determining an autocorrelation matrix T of this R for all pixels in the tile images T_L,

principal component analysis of the spectral reflectance can be performed statistically.

The principal components to be determined by principal component analysis are obtained by statistical treatments. To give an example, principal component vectors $p_k(\lambda)$ (k is an integer between 1 and n) which are eigenvectors of an orthonormalized autocorrelation matrix T consisting of n spectral reflectance values corresponding to n bands are determined as a plurality of sets with eigenvalues u_k (k = 1 to n) of the autocorrelation matrix T. The principal component vectors $p_k(\lambda)$ (k = 1 to n) are used to obtain a linear expansion of the spectral reflectance distribution $R(i,j,\lambda)$ for the tile images T_L at pixel position (i,j), as well as to determine the coefficients $s_k(i,j)$ (k = 1 to n) for the respective principal component vectors $p_k(\lambda)$ (k = 1 to n); thereafter, principal component images S_k (k = 1 to n) are obtained that use those coefficients as image data at the pixel position (i,j).

Principal component analysis is performed on the respective tile images T_L (L = 1 to n_t) and the principal component vectors $p_k(\lambda)$ (k = 1 to n) and the principal component images S_k (k = 1 to n) that have been obtained

for each tile image T_L (L = 1 to n_t) are sent to the optimum principal component vector/image extracting section 22c.

In the optimum principal component vector/image extracting section 22c, the principal component vectors $p_k(\lambda)$ (k = 1 to n) that have been obtained for each tile image T_L (L = 1 to n_t) in the principal component analyzing section 22b and the corresponding principal component images S_k (k = 1 to n) also obtained in 22b are used to determine an optimum principal component number m_1 for each tile image T_L (L = 1 to n_t), which is used to extract optimum principal component vectors $p_k(\lambda)$ (k = 1 to m_1) and optimum principal component images S_k (k = 1 to m_1) for each tile image T_L (L = 1 to n_t).

To be more specific, from the sets of the n principal component vectors $p_k(\lambda)$ (k = 1 to n) for the tile images T_L and the corresponding principal component images S_k (k = 1 to n), the sets of m (m < n) principal component vectors $p_k(\lambda)$ (k = 1 to m) and the corresponding principal component images S_k (k = 1 to m) are chosen and used to determine a composite image. The error in image information that may be possessed by this composite image

as compared with the original tile images T_L is used to
determine whether the m principal component vectors p_k (λ)
(k = 1 to m) and the corresponding principal component
images S_k (k = 1 to m) are really optimum principal
components.

The principal component vectors p_k (λ) for the tile
images T_L are such that the greater the corresponding
eigenvalue u_k, the greater the contribution the principal
component makes to the spectral reflectance distribution of
each tile image T_L. Considering this fact, the principal
component vectors $p_k(\lambda)$ are lined up in the decreasing
order of eigenvalue u_k and composite images are
reconstructed under a given illuminating light source by
adopting an increasing number of principal component
vectors having the larger eigenvalues u_k. In this process,
the error in image information the composite image has with
respect to the original tile images T_L each composed of n
principal component vectors decreases monotonically with
the increase in m, or the number of the principal component
vectors to be adopted. Therefore, the principal component
vector number m at which the above-mentioned error first
decreases below a predetermined value can be taken as a

minimum optimum principal component number m_1. As a result, the principal component vectors adopted to determine a composite image with the optimum principal component number m_1 and the principal component images obtained on the basis of these vectors can respectively be extracted as optimum principal component vectors $p_k(\lambda)$ ($k = 1$ to m_1) and optimum principal component images S_k ($k = 1$ to m_1) for the tile images T_L. Such optimum principal component vector $p_k(\lambda)$ ($k = 1$ to m_1) and optimum principal component image S_k ($k = 1$ to m_1) are determined for each tile image T_L.

The term "image information" as used herein means colorimetric values L*, a* and b* as measured in the CIEL*a*b* color space under a given light source such as the $CIED_{65}$ standard illuminant, and the "error" in such image information is the color difference ΔE_0 expressed by the following equation (1). The optimum principal component m_1 can be determined by finding the principal component image number m at which the color difference ΔE_0 is below a predetermined value, say, 1.0:

$$\Delta E_0 = \{(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2\}^{1/2} \qquad (1)$$

where ΔL^*, Δa^* and Δb^* represent the differences the

composite image has with respect to the tile images T_L in

terms of the average colorimetric values L^*, a^* and b^*

measured for all or part of the image. Thus, the optimum

principal component number m_1 is adaptively determined on

the basis of the color differences ΔE_0 between the

colorimetric values of the composite image in a color space

and those of the original image.

The error in the image information may be the square

error E_1 from the original image of the spectra for the

pixels in all or part of the tile images of the composite

image reconstructed by the m principal component vectors

p_k. The image data for the spectra having spectral

information in correspondence with the bands of the

composite image can also be regarded as an example of

colorimetric values and the optimum principal component

number m_1 may be adaptively determined on the basis of the

square error E_1 between the spectral image data that are

the colorimetric values of the composite image in a color

space and the spectral image data which are the

colorimetric values of the original image. Since the

square error E_1 or $\log(E_1)$ decreases monotonically with the

principal component vector number m, the optimum principal component number m_1 may be determined by increasing m and finding the value of m at which the amount of decrease in the square error E_1 or $\log(E_1)$ becomes smaller than a predetermined value, or a minimum value of m at which the decrease in the square error E with increasing m is saturated below a predetermined value may be substituted.

The obtained tile information consists of the optimum principal component number m_1, optimum principal component vectors $p_k(\lambda)$ (k = 1 to m_1) and the image data for the optimum principal component images S_k (k = 1 to m_1) is sent to the recording medium drive unit 24 as compressed multispectral image data together with the tile image information that was constructed when the multispectral image was segmented into tile images T_L in the image segmenting section 22a and which consists of the tile number of each tile image T_L, the tile position on the multispectral image, tile size (image size) of each tile image T_L and the pointer (address) for the tile information.

Having described the configuration of the system 10, we next describe the sequence of steps in the method of the invention for compressing multispectral images by the

system 10. The reader of the following description should refer to Fig. 4 for better understanding of the invention.

First, the object O is recorded with a multiband camera consisting of the light source 12, variable filter 14 and CCD camera 16 to acquire a multiband image which consists of a plurality of band images corresponding to the n bands into which the recording wavelength range has been divided (step 100). The acquired multiband image is temporarily stored in the multiband image data storage unit 18 and then sent to the multispectral image acquisition unit 20.

The multispectral image acquisition unit 20 has one-dimensional look-up tables (1D-LUTs) typically constructed from the correspondence between the image data for gray patches on a Macbeth chart and the values of their spectral reflectance. Using these 1D-LUTs as well as the image data for the multiband image of the object O that has been retrieved from the multiband image data storage unit 18, the unit 20 estimates the pixel-based spectral sensitivities of the object O and acquires the image data for the multispectral image (step 102). To estimate a highly precise spectral reflectance distribution for the

object O, deconvolution may optionally be performed by matrix operations and Fourier transformation.

In the next step 104, the image data for the multispectral image is segmented in a tile format to produce tile images T_L (L = 1 to n_t). At the same time, tile image information as header information is constructed and this information comprises the tile number of each tile image T_L, the tile position on the multispectral image, the tile size (image size) of each tile image T_L and the pointer (address) for the tile information (to be described later) which consists of the optimum principal component number m_1, optimum principal component vectors $p_k(\lambda)$ and the image data for the optimum principal component images S_k.

As Fig. 3 shows, all tile images T_L (L = 1 to n_t) have identical image size from the viewpoint of easy processing. If desired, in order to increase the compression ratio, the size of the tile images M_L may be varied as appropriate for the contents of the original image.

In the next step 106, principal component analysis is performed for each of the tile images T_L (L = 1 to n_t) in order to determine principal component images S_k (k = 1 to

n) and principal component vectors $p_k(\lambda)$ (k = 1 to n). The process of this principal component analysis is described below.

At the pixel position (i,j), each tile image T_L has a spectral reflectance distribution having n spectral reflectance values. If this spectral reflectance distribution is written as $R(i,j,\lambda) = [R(i,j,\lambda_1), R(i,j,\lambda_2), R(i,j,\lambda_3), \cdots, R(i,j,\lambda_n)]^T$ (superscript T represents transposition), calculation is made to determine an autocorrelation matrix T ($T_{i,j}$, or (i,j) component of T, is $R^T \cdot R/n$) for all pixels in the image or part of them, for example, the pixels that are left intact after pixel elimination at given intervals.

The thus obtained autocorrelation matrix T is a square (n x n) matrix and can be used to determine eigenvalues u_k ($u_1 > u_2 > \cdots > u_n$, k = 1 to n) and principal component vectors $p_k(\lambda)$ that satisfy the following equation (2). The principal component vectors $p_k(\lambda)$ are orthonormalized eigenvectors and expressed by $[p_k(i,j,\lambda_1), p_k(i,j,\lambda_2), p_k(i,j,\lambda_3), \cdots, p_k(i,j,\lambda_n)]^T$ (k = 1 to n). Methods for determining eigenvalues and eigenvectors are not limited to any particular types and various known methods may be

employed, as exemplified by the Jacobi method and the power method.

$$T \cdot p_k(\lambda) = u_k p_k(\lambda) \qquad (2)$$

As the following equation (3) shows, the spectral reflectance distribution $R(i,j,\lambda)$ at pixel position (i,j) is expressed by principal component vectors $p_k(\lambda)$ ($k = 1$ to n) which are eigenvectors:

$$R(i, j, \lambda) = \sum_{k=1}^{n} s_k(i, j) p_k(\lambda) \qquad (3)$$

Since principal component vectors $p_k(\lambda)$ ($k = 1$ to n) are orthonormal to each other, $s_k(i,j)$ can be determined from the following equation (4):

$$s_k(i,j) = R(i,j,\lambda) \cdot p_k(\lambda) \qquad (4)$$

where the dot represents the inner product of n-component vectors for the value of band's spectral reflectance, and $s_k(i,j)$ is the quantity representing the magnitude of the kth principal component vector p_k contained in the spectral reflectance $R(i,j,\lambda)$ of the multispectral image at pixel position (i,j). The value of $s_k(i,j)$ is calculated at each pixel position and the kth principal component image S_k ($k = 1$ to n) is then determined that has the calculated values

of $s_k(i,j)$ as the image data at the respective pixel positions.

As already mentioned, the contribution made by the first to nth principal components in the spectral reflectance distribution $R(i,j,\lambda)$ decreases with decreasing eigenvalue u_k that accompanies each principal component. Hence, to the extent that it holds the image information in an optimum manner, the spectral reflectance distribution $R(i,j,\lambda)$ can be approximated without the principal component vectors p_k having smaller eigenvalues u_k.

This method of approximation is expressed by the following equation (5); the eigenvalues u_k (k = 1 to n) are lined up in decreasing order and the eigenvectors $p_k(\lambda)$ (k = 1 to m) which correspond to the first m eigenvalues u_k (k = 1 to m) are adopted but the eigenvectors $p_k(\lambda)$ (k = m+1 to n) of the smaller eigenvalues are neglected; in this way, the spectral reflectance distribution $R(i,j,\lambda)$ is approximated and the image data is compressed accordingly:

$$R(i, j, \lambda) \fallingdotseq \sum_{k=1}^{m} s_k(i, j) p_k(\lambda) \qquad (5)$$

Based on this theory, the optimum principal component number m_1, or the number of principal component vectors p_k to be adopted that can approximate the spectral reflectance distribution $R(i,j,\lambda)$ without compromising the optimally held image information, is identified and used to compress the tile images T_L. As a result, the image data can be compressed without deteriorating the quality of the multispectral image.

In other words, the optimum principal component number m_1 which serves as a threshold for adopting the principal component vectors $p_k(\lambda)$ ($k = 1$ to m_1) which are eigenvectors of greater eigenvalues u_k but neglecting the eigenvectors $p_k(\lambda)$ ($k = m_1+1$ to n) having smaller eigenvalues and this is set by the following criterion for decision (step 108).

First, substitute the principal component vectors $p_k(\lambda)$ into Eq. (4) in the decreasing order of eigenvalue u_k and determine an approximate spectral reflectance distribution $R'(i,j,\lambda)$ which corresponds to the multispectral image, as expressed by the following equation (6):

$$R'(i, j, \lambda) = \sum_{k=1}^{m} s_k(i, j) p_k(\lambda) \qquad (6)$$

The approximate spectral reflectance distribution
$R'(i,j,\lambda)$ is not exactly the same as the spectral
reflectance distribution $R(i,j,\lambda)$ and contains some error.
However, if this approximate spectral reflectance
distribution $R'(i,j,\lambda)$ is multiplied by a specified
spectral intensity distribution to provide image
information about the composite image, the error presented
by this image information with respect to the image
information for the original image that is obtained by
multiplying the tile images T_L by the specified spectral
intensity distribution decreases with the increasing
principal component number m. Considering this fact, a
specified value is preliminarily set as the criterion for
decision and the minimum optimum principal component number
m_1 is acquired by determining the principal component
number m at which the error between the image information
about the composite image as obtained by multiplying the
approximate spectral reflectance distribution $R'(i,j,\lambda)$ by
a certain spectral intensity distribution and the image
information about the original image first becomes smaller

than the specified value which is set as the criterion for decision.

To give an example, the color differences ΔE_0 of colorimetric values L*, a* and b* in the CIE L*a*b* color space under the CIE D_{65} standard illuminant are taken as the error between the image information about the composite image and that about the multispectral image and a specified value is set for each of these color differences ΔE_0 and the minimum optimum principal component number m_1 is determined.

The error may be the square error E_1 of the spectra for all or part of the composite image. In this case, one may determine a minimum value of the optimum principal component number m_1 at which the decrease in the square error E_1 with increasing principal component number m is saturated below a predetermined value.

Thus determined is the minimum optimum principal component number m_1 which holds and optimally represents the image information about each of the tile images T_L and based on this number, one acquires m_1 optimum principal component vectors $p_k(\lambda)$ (k = 1 to m_1) corresponding to eigenvalues u_1 to u_{m1} (u_1 to $u_{m1} > u_{m1+1} > \cdots > u_n$), as well

as m_1 optimal principal component images S_k ($k = 1$ to m_1).
In comparatively many cases, the rejected principal
component vectors $p_k(\lambda)$ ($k = m_1+1$ to n) are predominantly
composed of the noise component in the tile images T_L and,
hence, the noise component in the multispectral image can
be suppressed by rejecting the less contributing principal
component vectors $p_k(\lambda)$ ($k = m_1+1$ to n) from the tile
images T_L.

Thus, in step 108, the optimum principal component
number, optimum principal component vectors $p_k(\lambda)$ and the
image data for the optimum principal component images S_k
are obtained for each of the tile images T_L ($L = 1$ to n_t)
and together with the tile image information constructed in
step 104, this tile information is sent to the recording
medium drive unit 24 where they are recorded and stored on
a recording medium such as hard disk, floppy disk, MO, CD-R
or DVD (step 110). In the embodiment under consideration,
the multispectral image is segmented into tile images T_L
and principal component analysis is performed for each tile
image T_L and this offers a particular advantage in that if
the tile images T_L do not change greatly in hue, lightness
or saturation, the optimum principal component number m_1

suffices to be 1 or 2 and this means that only one or two optimum principal component vectors p_k are necessary to hold and optimally represent the image information. As a result, the image data for the multispectral image can be compressed at a higher ratio without sacrificing the quality of the image.

After determining the optimum principal component number m_1 and acquiring both the optimum principal component vectors $p_k(\lambda)$ ($k = 1$ to m_1) and the optimum principal component images S_k ($k = 1$ to m_1) in step 108, the optimum principal component images S_k ($k = 1$ to m_1) may optionally be subjected to further image compression by a suitable technique such as the JPEG (Joint Photographic Experts Group) technique, or compressed to an even higher ratio by huffman coding or any other known arithmetic coding techniques.

Using the above-described multispectral image compressing method and apparatus, the present inventors made an experiment of multispectral image compression in the following manner.

CA-D4-1024A of DALSA (1024 x 1024 pics each sized to 12 x 12 microns; furnished with PCI interface; monochromatic) was used as CCD camera 16, and Varispec

Tunable Filter (liquid-crystal tunable filter of CRI) as variable filter 14. By means of this apparatus, the recording wavelength range of from 380 to 780 nm was divided by 10 nm into 41 bands (n = 41). The object O was a person standing outdoors who was recorded with the CCD camera 16 to take a multiband image of the person consisting of 41 band images.

The multiband image storage section 18, multispectral image acquisition unit 20 and multispectral image compressing unit 22 were implemented in a notebook PC (personal computer) of PROSIDE and processing with software was executed on Windows 95 in C^{++}. The CPU in the PC ran at 166 MHz and the RAM had a capacity of 128 Mbytes.

To provide convenience in processing with software, the image data quantization number was changed from 2 bytes to 1 byte in a preliminary treatment, which was not included in the process of compressing the volume of image data to be described below.

First, a multispectral image having 41 constituent wavelength bands was extracted from the multiband image that had been sent to the multispectral image acquisition unit 20. The extracted multispectral image consisting of

1024 x 1024 pixels was segmented into tile images T_L (L = 1 to 4096) each consisting of 16 x 16 pixels.

Principal component analysis was performed each of the tile images T_L (L = 1 to 4096) to determine principal component vectors $p_k(\lambda)$ (k = 1 to 41) and principal component images S_k (k = 1 to 41).

Then, in order to determine the optimum principal component number m_1, a value of 1.5 in terms of the average color difference based on chromaticity in the CIE D1976 L*a*b* color space under the CIE D_{65} standard illuminant was chosen as the criterion for decision. In the decreasing order of eigenvalues u_k obtained by the principal component analysis, the m corresponding principal component vectors $p_k(\lambda)$ (k = 1 to m) were sequentially adopted. After reconstructing a composite image on the basis of these principal component vectors p_k, the above-defined average color difference from the original image composed of the tile images T_L was determined and an optimum principal component m_1 was also determined at which the average color difference was below 1.5.

As it turned out, the optimum principal component number m_1 for the tile images T_L (L = 1 to 4096) was

between 2 and 6. In the case of the tile image T_B shown in Fig. 3 which is in a blank area that has small changes in hue, lightness and saturation and which is part of the background of the human object O or in the case of a tile image T_L having identical hue, lightness and saturation, the optimum principal component number m_1 was smaller than in the case of the tile image T_A also shown in Fig. 3 and a value of 2 was sufficient; in other words, the tile images T_L could be expressed by the first principal component vector $p_1(\lambda)$ and the second principal component vector $p_2(\lambda)$. When a less stringent criterion was used, the first principal component vector $p_1(\lambda)$ was sufficient to hold and represent the original image information in an optimal way.

In the next step, tile image information is added to the optimum principal component number m_1, optimum principal component vectors $p_k(\lambda)$ and optimum principal component images S_k for each tile image T_L and the tile image information consists of the tile number of tile image T_L, the tile position on the multispectral image, the tile size (image size) of tile image T_L and the pointer (address) for the tile information consisting of said optimum principal component number m_1, optimum principal

component vectors $p_k(\lambda)$ and the image data for the optimum

principal component images S_k. The combined data is

recorded and stored via the recording medium drive unit 24.

As a result, the image data was reduced from about 41

Mbytes to 4 Mbytes, which was less than a tenth of the

initial volume. The compressed image data was later

retrieved and a composite image was reconstructed but no

visual deterioration in image quality was observed.

Obviously, it is clear that the image compressing

method according to the first aspect of the invention and

the image compressing apparatus using it can compress a

plurality of spectral images at a higher ratio, say, about

10:1 without causing any visual deterioration and thus

contribute to more efficient handling of image data.

While the multispectral image compressing method and

apparatus of the invention have been described above in

detail, it should be noted that the foregoing embodiment is

not the sole case of the invention and various improvements

and modifications are possible without departing from the

scope and spirit of the invention.

As described above in detail, according to the present

invention, a multispectral image of high data volume is

segmented into a plurality of tile images, principal